

PSG DYNAMIC CHANGES IN METHAMPHETAMINE ABUSE USING RECURRENCE QUANTIFICATION ANALYSIS

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ABSTRACT: Polysomnography (PSG) is a standard approach based on comprehensive monitoring of cardiorespiratory signals during sleep. This study has been conducted on subjects with a record of methamphetamine abuse. The significance of this work is methamphetamine abuse detection and measurement without the use of blood tests. With regard to the nonlinear and chaotic dynamic of vital signals and the richness of PSG, the tool employed to carry out the study is Recurrence Qualification Analysis. The objective behind this is to observe and quantify nonlinear dynamic changes of vital signals caused by methamphetamine abuse. Results reveal that: 1) chaotic signals, in other words, system complexity has decreased; 2) under the influence of methamphetamine, signal entropy has increased, bringing about the irregularity of the signals; 3) methamphetamine consumption prompts signal compression to overtake signal expansion which means signal information has declined.

ABSTRAK: Polisomnografi (PSG) adalah pendekatan piawai berdasarkan pengawasan menyeluruh signal kardiorespiratori ketika tidur. Kajian ini telah dijalankan ke atas subjek yang mempunyai rekod salah guna methapitamin. Kepentingan kajian ini adalah bagi mengesan salah guna methapitamin dan mengukurnya tanpa menggunakan ujian darah. Dengan mengambil kira ketidak-linear dan signal penting dinamik dan PSG yang berharga, kaedah yang digunakan bagi menjalankan kajian ini adalah Analisis Kelayakan Berulang. Objektif di sebalik kajian ini adalah bagi melihat dan mengkuantiti perubahan dinamik tidak linear ke atas signal penting disebabkan salah guna methapitamin. Hasil menunjukkan: 1) Signal huru-hara, atau kata lain, kesulitan sistem telah berkurang; 2) di bawah pengaruh methapitamin, signal entropi telah bertambah, menjadikan signal tidak normal; 3) pengambilan methapitamin menyebabkan signal mampat mengambil alih signal kembang bermaksud informasi signal telah berkurang.

KEYWORDS: *sleep apnea; methamphetamine; chaos; recurrence qualification analysis; polysomnography*

1. INTRODUCTION

Sleep apnea is a common breathing disorder in sleep during which the individual's breathing is disrupted. It lasts for several seconds or several minutes and occurs at least 5 times in an hour. Sleep apnea results in serious health problems such as excessive daily drowsiness, nonrestorative sleep, depression, decrease in memory, and even serious cardiac arrhythmias. Also, it has indirect effects on high blood pressure, brain stroke, and

myocardial infarction. Fortunately, sleep apnea is a curable disorder. However, the majority of patients suffering from it, comprising 6 percent of the whole world population, remain undiagnosed [1,2].

Polysomnography (PSG) is a standard approach based on comprehensive monitoring of cardiorespiratory signals during sleep which is used to detect sleep apnea. In PSG the following vital signals are simultaneously recorded: 1) EEG: electroencephalography; 2) EOG: electrooculogram, 3) EMG: electromyography; 4) ECG: electrocardiography; 5) air flow through the nose, stomach, and the chest; 5) snoring and oxygen-rich blood (SPO). Studying vital signals of the body yields valuable information on bodily behavior. In recent years, nonlinear methods of analyzing physiological signals have replaced traditional methods, such as Fourier transport and wavelet transport. This is mainly because physiological rhythms of the body are nonlinear, chaotic, and unstable. In other words, the characteristics of physiological signals change with the passage of time and these changes are not regular. On the basis of the research carried out in this field, when a bodily disorder occurs, system behavior becomes more predictable and regular while system disorder decreases. In the past, to analyze sleep apnea, numerous research works were conducted on different organs of the body, particularly on the heart and its various parameters such as the number of heart beats. The human brain is the control center of every bodily activity while, on the other hand, the body's metabolism influences the brain. Accordingly, influential factors on metabolism (such as methamphetamine) affect the cerebral dynamic signals. This study is particularly conducted on subjects with a record of methamphetamine abuse. According to studies carried out on PSG, especially on bodily behaviors during sleep, subjects with a record of methamphetamine abuse suffer from problems such as decrease in sleep time, nonrestorative sleep, decrease in the healthy functioning of the body, and an increase in mortality rate [3,4].

It is widely believed that sleep apnea is caused by narcotic drugs such as opium, heroin, and morphine. However, recent studies reveal that methamphetamine, too, can cause sleep apnea. In December 28, 2012, research was conducted on 535 people addicted to methamphetamine hydrochloride that revealed 40 subjects were experiencing apnea. The rate of apnea among the subjects was 7.48 percent [2].

2. METHODOLOGY

2.1 Data Collection

This study is particularly conducted on subjects with a record of methamphetamine abuse. According to studies done on PSG [5], and especially on physiological behaviors during sleep, subjects with a record of methamphetamine abuse suffer from problems such as decrease in sleep time, nonrestorative sleep, decrease in the healthy functioning of the body, and an increase in mortality rate [6]. To record PSG and analyze sleep apnea, it is necessary to hospitalize the patient overnight. The data used in this study are stored in the sleep clinic at Ibn Sina Hospital, Mashhad, Iran. To create this database, 13 subjects (aging 25 ± 5) were asked to stay overnight in the hospital. All the signals were sampled at 256 Hz which include a four-channeled EEG with four channels, a standard two-channeled EOG, EMG, ECG, heartbeat, chin movements, left and right leg movements, blood oxygen, respiration signals, snore signals, and thorax and abdominal signals. The database that we record for this research includes 13 subjects with 5 (Control Group) CG subjects whose health has been confirmed by a doctor and 8 (Methamphetamine Group) MG with a record of methamphetamine abuse.

2.2 Curve Recurrence Tools for Analyzing Data

Recurrence is a fundamental property of dynamic systems that can be exploited to determine the behavior of the system in the phase space [7]. Recurrence as a scientific element was introduced by Henry Poincare in 1980. He was the first to prove that the three-body problem was chaotic and unsolvable. When working on the three-body problem, Poincare stated that, irrespective of some exceptional trajectories whose occurrences were infinitely improbable, it could be shown that the system recurrently returns to a point very close to its starting point. In 1987, Eckmann et al. [8,9] introduced the method of recurrence plots (RP) in order to concretize the recurrences in dynamic systems. Let us assume that there is the trajectory \vec{x}_i (consisting of N points) of a system in its phase space. The system development is, therefore, described by a series of vectors that denote a trajectory in a virtual mathematical space. The corresponding recurrence curve, then, is based on the following recurrence matrix:

$$R_{i,j} = \begin{cases} 1: \vec{x}_i \approx \vec{x}_j, \\ 0: \vec{x}_i \not\approx \vec{x}_j, \end{cases} \quad i, j = 1, \dots, N, \quad (1)$$

Where N is the number of considered states of $\vec{x}_i \approx \vec{x}_j$, considering the error distance ε . Regarding the fact that the system does not exactly recur to a previously observed state, ε is essential.

RP can be defined as follows:

$$R_{i,j}(\varepsilon) = \Theta(\varepsilon - \|\vec{x}_i - \vec{x}_j\|), \quad i, j = 1, \dots, N, \quad (2)$$

Where N is the number of \vec{x}_i calculated points, $\|\cdot\|$ is the norm, and $\Theta(\cdot)$ is the Heaviside function (meaning that if $x < 1$, then $\Theta(x) = 0$, and in other points $\Theta(x) = 1$).

To compute RP, a proper norm has to be chosen. The norms that are frequently exploited are $L1$, $L2$ norms (the Euclidean norm), and the L_∞ norm (Maximum or Supremum norm). Since ε is fixed, L_∞ , $L1$, and $L2$ find the most, the least, and the intermediate amount of neighbors respectively. To compute RP, L_∞ is often used, because it computes fast and allows us to study RP features analytically. ε can have a fixed value or it can vary. Choosing a proper ε is of great importance, because if ε is too small, there will be almost no RP, and if ε is too large, RP will experience too much disturbance, causing thicker and longer diagonal structures. Some criteria for choosing ε are introduced:

- 1) A few percentage of the suggested maximum phase space diameter (usually less than 10 per cent of the mean) [9,10].
- 2) Taking into account the density of the recurrence points by seeking a scaling region in the density of the recurrence points [8].
- 3) Measuring a composition of real signals and observable noise with standard deviation (to get similar results in noise-free situations, ε needs to be chosen so that it is five times greater than the standard deviation: $\varepsilon > 5\sigma$. This criterion, which is useful for de-noising, minimizes fragmentation and the thickness of the diagonal lines in accordance with the threshold [9].
- 4) Using constant density of the recurrence points: the FAN method is suitable to be used for bodily signals since it does not necessitate the presence of soakers with similar volume and capacity to compare state space behaviors [10].

2.2.1 Complexity Criteria (Recurrence Qualification Analysis RQA)

To move beyond the visual impressions obtained from RPs, several qualitative complexity criteria of small scale structures are presented in RPs that are known as recurrence qualification analysis. On the basis of the density of the recurrence points, these measures include structures of diagonal lines of length l , meaning that the two trajectory segments were running tangentially within the neighboring distance of ϵ for l time units, and structures of vertical lines of length ν , showing that the trajectory does not change considerably for ν time units.

1) Criteria based on recurrence density

Recurrence rate: the simplest criterion of recurrence curves is recurrence rate (RR) or recurrence percentage, which is calculated as in equation 3:

$$RR(\epsilon) = \frac{1}{N^2} \sum_{i,j=1}^N R_{i,j}(\epsilon), \tag{3}$$

which is a measurement of the density of the recurrence points in RP.

2) Criteria based on diagonal lines

Determinism: uncorrelated or weakly correlated processes with accidental relations or with chaotic behavior are the causes behind the formation of very short diagonals, while deterministic processes form longer diagonals and isolated recurrence points. The ratio of diagonal recurrence points (from minimum length L_{min}) to all recurrence points is introduced as the criterion of the system's determinism.

$$DET = \frac{\sum_{l=L_{min}}^N IP(l)}{\sum_{l=1}^N IP(l)} \tag{4}$$

The threshold excludes the L_{min} of diagonal lines that are formed by parallel movements in the phase space trajectory. For $L_{min} = 1$, determinism is equal to one. Nevertheless, if L_{min} is too large, the histogram of $P(1)$ can become scattered, and consequently, determinism's reliability decreases.

On the basis of the histogram, $P(\epsilon, L)$ of diagonal lines is L , that is

$$P(\epsilon, l) = \sum_{i,j=1}^N (1 - R_{i-1,j-1}(\epsilon))(1 - R_{i+1,j+1}(\epsilon)) \prod_{k=0}^{l-1} R_{i+k,j+k}(\epsilon). \tag{5}$$

Sometimes for reasons of simplicity, the symbol ϵ is eliminated from the RQA (that is, $P(\epsilon, l) = P(l)$).

- The average diagonal line length (L): it is the average time that two trajectory segments are close to each other and can, thus, be interpreted as the average prediction time.

$$L = \frac{\sum_{l=L_{min}}^N l IP(l)}{\sum_{l=L_{min}}^N IP(l)} \tag{6}$$

Where $N_l = \sum_{l \geq L_{min}} P(l)$ is the total number of diagonal lines. This criterion is related to the divergence of the phase space trajectory.

- The length of the longest diagonal line (L_{max}): another RQA criterion is taking into consideration the length of the longest diagonal line in the RP.

$$L_{\max} = \max(\{l_i\}_{i=1}^{N_1}), \tag{7}$$

The faster the segments of the trajectory diverge, the shorter the diagonal lines become.

- Entropy: it refers to the Shannon entropy with the probability of $p(l) = P(l)/N_1$ which is exploited to find a diagonal line with the exact length of L in the recurrence curve.

$$\text{ENTR} = - \sum_{l=l_{\min}}^N P(l) \ln P(l) \tag{8}$$

Entropy shows the complexity of the RP with respect to diagonal lines. For instance, for uncorrelated noise, the value of the entropy is almost small, which points to its low complexity.

3. Criteria based on vertical lines

- Laminarity (LAM): similar to determinism, it is the ratio of the vertical lines recurrence points to the total number of recurrence points. It is calculated as follows:

$$\text{LAM} = \frac{\sum_{v=v_{\min}}^N vP(v)}{\sum_{v=1}^N vP(v)}, \tag{9}$$

Computing LAM can be done only by those values of V that are greater than the minimal length V_{\min} so that the effect of tangential movement declines. For maps, $V_{\min} = 2$ is a good value. LAM criterion illustrates the instances of laminar states in the system without describing the length of these laminar phases. If RP includes more single recurrence points than vertical structures, LAM decreases.

- Trapping Time (TT): The average length of vertical structures is calculated as in the following equation:

$$\text{TT} = \frac{\sum_{v=v_{\min}}^N vP(v)}{\sum_{v=v_{\min}}^N P(v)}, \tag{10}$$

which is referred to as trapping time. Computing this criterion requires taking into consideration a minimal length V_{\min} (as in LAM). TT is the mean time that a system remains stable in a particular state. It can also estimate for how long a state can remain trapped.

- The length of the longest vertical line (V_{\max}): it is similar to L_{\max} in diagonal lines.

$$V_{\max} = \max(v_l |_{l=1}^{N_y}) \tag{11}$$

where N_y is the absolute number of vertical lines.

Contrary to criteria based on diagonal lines, these criteria can detect chaos-chaos transitions. Consequently, it allows intermittency for even short and non-stationary data series to be investigated. Moreover, since measures that quantify the vertical structures for periodic dynamics are zero, it is easier to detect chaos-chaos transitions [11].

- Recurrence points of first type (T1): Consider a special state like \vec{x}_1 . Then, assuming that

$$B_{\varepsilon_i}(\vec{x}_i) = \{\vec{x}: \|\vec{x} - \vec{x}_i\| \leq \varepsilon_i\} \tag{12}$$

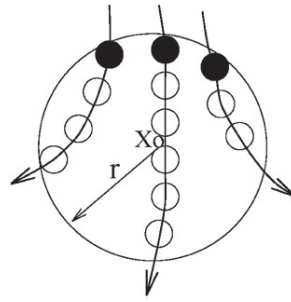


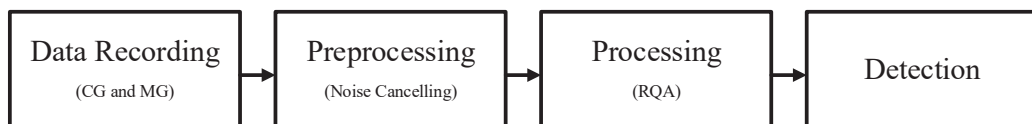
Fig. 1: Recurrence points of the first type, each arrow is a trajectory.

$B_{\varepsilon_i}(\vec{x}_i)$ illustrates a set of recurrence points that includes the entire set of points in Fig. 1. These recurrence points show a sequence in the order of their appearance on a trajectory. For instance, $\{\vec{x}_{t_1}, \vec{x}_{t_2}, \dots, \vec{x}_{t_{B_i}}\}$, where B_i is the number of elements in $B_{\varepsilon_i}(\vec{x}_i)$. Accordingly, the recurrence time of the first type (T_1) is the average of all $t_{j+1} - t_j, j = 1, \dots, B_i - 1, i = 1, \dots, N$. It calculates the evolution of constructed state phases.

- Recurrence points of the second type: these are the points that are entering $B_{\varepsilon_i}(\vec{x}_i)$ from outside. In Fig. 1 these points are shown by the black dots.

This trajectory might stay within the neighborhood for some time, meaning that it forms a sequence of points represented by the open dots in Fig. 1. These points are called sojourn points¹. The recurrence time of the second type (T_2) is the average of time difference between the neighboring black dots on a trajectory, which is the system’s required average time in order for it to recur to a particular state after eliminating the sojourn points.

Data sets are analyzed as in the diagram below.



3. RESULTS

As mentioned earlier, the primary aim of RPs is to concretize the trajectories in phase space, which is particularly beneficial to systems with large dimensions. With the passage of time, RPs provide valuable insights into these systems because normal patterns in RPs are related to special behaviors of the system. Respiratory disruptions that last from 20 seconds to one minute usually occur intermittently in the space of 5 minutes or more. Thus, respiratory dynamics occur periodically during sleep. As illustrated in Fig. 2, the RP of CG subjects (the figure on the right) consists of ordered and regular vertical and diagonal lines. But in the RP of the MG, white areas in Recurrence diagram denote sudden changes are observed in the dynamics.

¹States of subsequent time may fall into the neighbourhood of the state at time i , pretending artificial recurrences (grey dots). This is called tangential motion and such points are referred to as sojourn points [10].

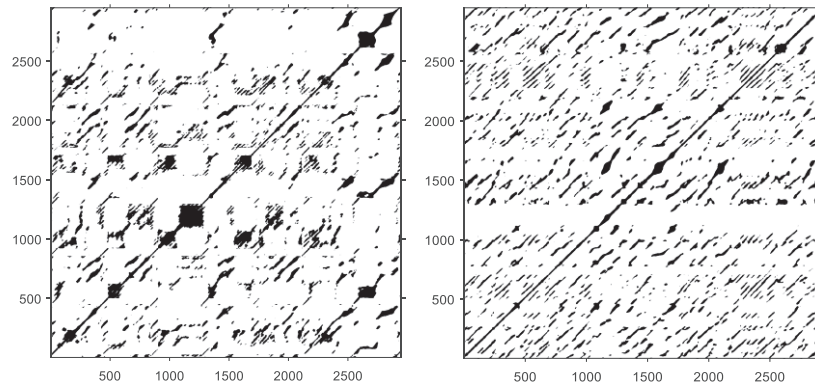


Fig. 2: EEG Recurrence diagram from F4 electrode. On the right is (Control Group) CG and on the left is (Methamphetamine Group) MG.

The recurrence diagram in Fig. 2 is related to the EEG signal from channel F4 of the healthy subject and the one on the left belongs to the subject with a record of methamphetamine abuse. As it is illustrated, the figure on the right (the healthy subject) includes vertical and regular diagonal lines while in the RP of the patient, white zones or stripes indicate sudden changes in the dynamic.

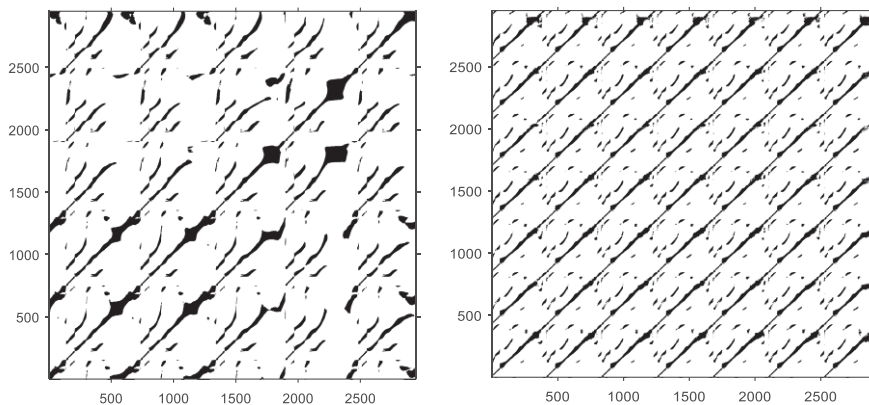


Fig. 3: EEG recurrence signal diagram from lead electrode. On the right is (Control Group) CG and on the left is (Methamphetamine Group) MG.

The recurrence diagram in Fig. 3 is related to the EEG signal of the healthy subject and the subject with a record of methamphetamine abuse. As a result of methamphetamine abuse, the changeability of the (HRV) EEG signal has declined, and the ECG signal has changed from a chaotic state to a quasi-periodic state.

As mentioned before, RQA refers to quantified values describing the structure of recurrence curves. Normally, there are ten values used in RQA: recurrence rate (RR), determinism (DET), maximum diagonal line length (L_{max}), maximum vertical line length (V), entropy of the distribution of the diagonal lines (ENTR), average length of diagonal lines (L), Laminarity (LAM), trapping time (TT), recurrence time of the first type (T_1), and recurrence time of the second type (T_2). In this study the proposed method to choose neighbors is FAN (fixed amount of nearest neighbors). As it was discussed earlier, by choosing FAN to compute recurrence plots, the determined threshold ε_i would change at every state, such that there exists a fixed number of recurrence points for each \vec{x}_i of the

RPs. This indicates that an RP is always fixed. Therefore, in this study, only nine measures of RQA are exploited as features. As illustrated in Tables 1 and 2, the value of all the features of the normal subject is higher. This is due to the decrease of non-linear interrelations in normal subjects. It is also observed that mean and standard deviation in RR are fixed. Most of the meaningful differences belong to L (the average length of diagonal lines), ENTR, and T₂. L is the average time that two trajectory segments are close to each other, and can be interpreted as the mean prediction time. Entropy is used to find a diagonal line of the exact length of L in the RP. Entropy shows the complexity of RPs with respect to diagonal lines (as shown in part 2-2-1 these parameters did not have units).

Table 1: Mean and standard deviation of RP in EEG signal of C3 channel

EEG3	RR	DET	L	L _{max}	ENTR	LAM	TT	V _{max}	T1	T2	
MG	mean	0.0980	0.9905	19.1365	966.5133	3.6213	0.9918	12.7628	64.0933	7.5694	106.326
	var	0.0081	0.0814	3.5343	79.4451	0.3569	0.0815	1.8599	11.6621	0.8683	16.21226
CG	mean	0.0980	0.9913	24.3466	966.5133	3.8809	0.9922	13.1054	59.0067	7.9481	116.3217
	var	0.0081	0.0815	5.1310	79.4451	0.4263	0.0816	1.8817	11.4461	0.8310	17.59166

Table 2: Mean and standard deviation of RP in ECG signal

EEG3	RR	DET	L	L _{max}	ENTR	LAM	TT	V _{max}	T1	T2	
MG	mean	0.0980	0.9905	23.8587	966.5133	3.7902	0.9924	15.8588	62.1000	7.9072	142.7364
	var	0.0081	0.0814	2.8912	79.4451	0.3260	0.0816	1.4517	11.2577	0.7499	14.1170
CG	mean	0.0980	0.9915	33.5127	966.0733	4.0865	0.9925	20.5995	72.6333	6.8875	167.8453
	var	0.0081	0.0815	5.9778	79.5916	0.3663	0.0816	3.0648	11.5772	0.9024	22.9307

Since apnea can cause disturbances in the balance and the regularity of the heart during sleep, using ECG signals to detect sleep apnea is very useful. Furthermore, it is believed that the recurrence points derived from ECG signals are immune to the effects of the non-stationary nature of nonlinear time series. Therefore, it can be used as a proper tool in detecting methamphetamine abuse. Comparing Tables 1 and 2 indicate that the change in ECG signal is more obvious in comparison with the EEG signal, meaning that methamphetamine (at least in the examined subjects) has a greater effect on the heart than on the brain. In other words, RQA reveals changes in the dynamics of heart signals more than it reveals changes in the brain signals. Results point to palpable changes in the nonlinear dynamic of vital signals (especially heart and brain signals) caused by methamphetamine abuse. As a result of methamphetamine consumption, measures such as the average length of diagonal lines, entropy, and recurrence points of the second type are increased. This indicates that, firstly, due to methamphetamine consumption, the predictability of signals has increased. In other words, signal complexity has declined. Secondly, as a result of methamphetamine consumption, signal entropy has grown. The increase of entropy brings about the increase of signal irregularity. Thirdly, methamphetamine consumption occasions signal compression more than its expansion. This means that signal information has decreased.

3.1 Statistical Analysis

In this study we have used T test statistical analysis. In independent samples, a T test is obtained by dividing the difference between the means of the samples and the standard deviation of the distribution of differences (known as the standard error of the difference). T test assumes that the data have been collected from normal distribution with equal variance. The result of this test is reflected in the p value. If p tends towards zero, it

becomes obvious that the zero hypothesis is rejected at the level of 5 per cent, and if it tends towards one, it will be against the zero hypothesis at the level of 5 per cent.

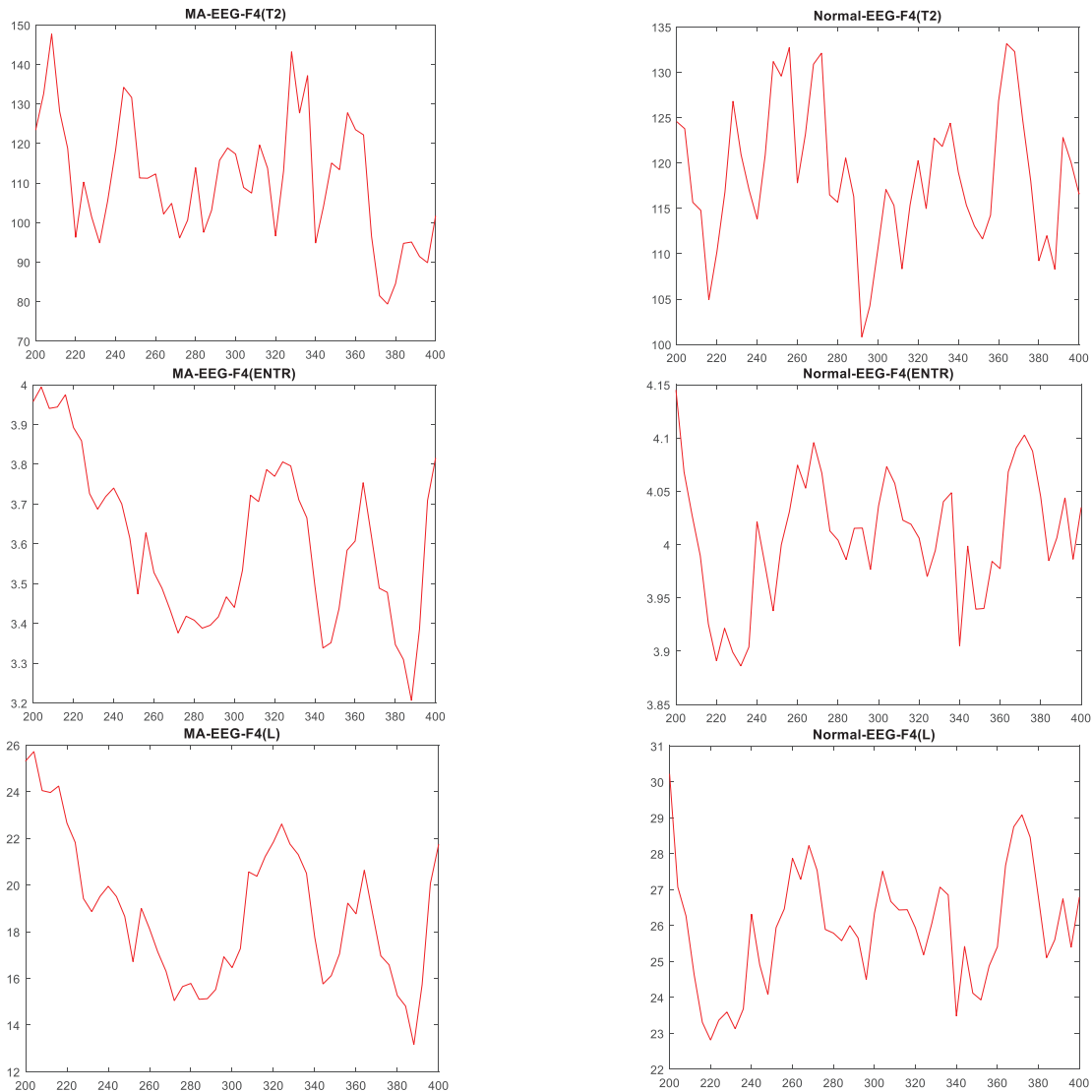


Fig. 4: Recurrence ENTER (up figures) and L (down figures) parameters in F4 channel of EEG signal of MG (on the left) and CG (on the right).

To compare the signals of normal subjects with those of the ones under the influence of methamphetamine abuse on PSG signals, the above-mentioned measures, such as RR, determinism (DET), maximum diagonal line length (L_{max}), maximum vertical line length (V), entropy of the distribution of the diagonal lines (ENTR), average length of diagonal lines (L), Laminarity (LAM), trapping time (TT), recurrence time of the first type (T_1), and recurrence time of the second type (T_2) are obtained, which identify signal behavior. Then, T-test was used to investigate the degree of the meaningfulness of the difference in these measures both in normal subjects and in patients (Table 3). This result is in accord with the ones we obtained directly from the nonlinear recurrence plots. The best measures that reveal the most differences between the two classes are L, ENTR, TT, and T_2 . These measures are formed based on diagonal and vertical lines, and show chaos-chaos [12] and chaos-order transitions respectively.

In Table 3 the extracted P-Value features are specified according to nonlinear values of 0.05. As it is seen, the L, ENTR, TT, T₂ measures reveal the most differences between the two classes. These values show chaos-chaos and chaos-order transitions respectively.

For example, L is the average time that two trajectory segments are close to each other and can, thus, be interpreted as the average prediction time and in all PSG signals, we could see MG signals have deterministic behaviors and therefore show significant difference between CG and MG.

Table 3: P-Value in comparing control group with the group affected by methamphetamine abuse

Signal	Feature	RR	DET	L	L _{max}	ENTR	LAM	TT	V _{max}	T1	T2
EEG	F3	1	0.9662	10 e -5	1	0.0105	0.9903	10 e -5	10e -5	10e -5	0.2472
	F4	1	0.9621	10 e -5	1	0.0010	0.9911	10 e -5	10e -5	10e -5	0.3708
	C3	1	0.9266	10 e -5	1	10e -5	0.9652	0.1139	0.0002	0.0001	10 e -5
	C4	1	0.9280	10 e -5	1	10e -5	0.9652	0.1675	0.0004	0.0423	0.0007
	O1	1	0.9513	10 e -5	1	10 e -5	0.9825	0.8043	0.0014	0.3677	0.3057
EOG	O2	1	0.9371	10 e -5	1	10 e -5	0.9671	10 e -5	0.0320	0.6149	10 e -5
	E1	1	0.8349	10 e -5	1	10 e -5	0.9146	0.0001	0.8429	0.8225	010 e -5
	E2	1	0.6880	10 e -5	0.4201	10 e -5	0.8220	10 e -5	0.1779	0.0032	010 e -5
ECG		1	0.9196	10 e -5	0.9618	10 e -5	0.9867	10 e -5	10 e -5	10 e -5	010 e -5
CHIN (as PSG protocol)		1	10 e -5	0.1332	0.0053	0.3072	10 e -5	0.0466	0.3182	0.1195	010 e -5
ABDO (as PSG protocol)		1	10 e -5	10 e -5	10 e -5	10 e -5	0.8813	10 e -5	10 e -5	10 e -5	010 e -5
Flow (as PSG protocol)		1	0.1060	10 e -5	1	10 e -5	0.9861	10 e -5	10 e -5	10 e -5	010 e -5
Pflow (as PSG protocol)		1	10 e -5	10 e -5	10 e -5	10 e -5	0.6264	10 e -5	10 e -5	10 e -5	10 e -5
Rleg (as PSG protocol)		1	0.0007	10 e -5	10 e -5	10 e -5	10 e -5	10 e -5	10 e -5	0.0793	10 e -5
Lleg (as PSG protocol)		1	10 e -5	0.0014	10 e -5	10 e -5	10 e -5	10 e -5	0.0724	0.0652	10 e -5
HR		1	0.9972	0.1626	0.7422	0.1469	0.9979	0.2083	1	0.1737	0.7200
Spo2		1	0.9975	0.0050	0.0005	10 e -5	0.9991	0.0093	1	0.0065	0.0274
Snore		1	10 e -5	10 e -5	10 e -5	10 e -5	0.8350	0.2640	0.5546	0.0982	0.0181
Thor (as PSG protocol)		1	0.9740	10 e -5	1	0.3218	0.9867	10 e -5	10 e -5	10 e -5	10 e -5

P-value less than 1e-4

4. CONCLUSION

Methamphetamine abuse has increased dramatically during the past decade, this could be detected with PSG signals without blood testing. Methamphetamine abuse affects sleep and we could measure this with efficacy. RQA parameters show signals' chaotic behaviors and this research displays that self-organization in PSG signals are affected with methamphetamine abuse.

5. COMPLIANCE WITH ETHICAL STANDARDS

5.1 Ethical Approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

5.2 Informed Consent

Informed consent was obtained from all individual participants included in the study.

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